JEE Journal of Ecological Engineering

Journal of Ecological Engineering, 2025, 26(2), 73–84
https://doi.org/10.12911/22998993/195972
ISSN 2299–8993, License CC-BY 4.0

Received: 2024.10.20
Accepted: 2024.12.15
Published: 2025.01.01

Evaluation of the life cycle and determining the degree of firmness and acidity of rose apple with image processing and neural network with the grey wolf method to predict environmental effects

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ABSTRACT

This study evaluates the process of detecting the degree of firmness and pH of rose apples with the help of image processing from the point of view of environmental effects. The process of this study started with image processing. In image processing, the selected samples were photographed with a charge-coupled device (CCD) camera, and red (R), green (G), and blue (B) values were extracted with the image processing algorithm in MATLAB software. Next, the hardness and acidity values of the samples were extracted using laboratory steps. Next, with the inputs of each test, the life cycle assessment (LCA) list was prepared. Then, with the Impact 2002+ method, the list was subjected to life cycle evaluation, and the middle and final effects of the analyses were extracted. Next, the neural network and grey wolf optimizer (GWO) methods were used to predict environmental effects. Based on the results, it was determined that the values of R and G had the highest effect on estimating pH and the values of B and G had the highest effect on estimating the product's hardness. Also, the results of evaluating the accuracy of the artificial neural network combined with the grey wolf optimizer showed that the accuracy of the estimation of environmental effects in the evaluation of pH was about 3–5% higher than that of soluble solid content (SSC). Based on the findings, using the integrated machine learning (ML) system with image processing is a reliable method to estimate the environmental effects of detecting the quality characteristics of Iranian rose apples entirely non-destructively.

Keywords: machine learning, apple, image processing, life cycle assessment, non-destructive testing.

INTRODUCTION

Apple is one of the most well-known fruits for human use and one of the most essential horticultural products in the world [Bakhshi and Arakawa, 2006]. The production of the yellow apple type, which has nutritional and therapeutic value, is expanding [Matsumoto et al., 2021]. Therefore, according to this type of fruit's nutritional value and quality, it has played an important role among all kinds of fruits in terms of providing mineral elements, fiber, and sugars in human nutrition [Tahir and Jönsson-Balsgård, 2004]. On the other hand, various influential factors and parameters on the quality and condition of the nutritional compounds of yellow apples, such as region, climate, fertilizer, and genetic properties, have been the focus of experts and researchers, and today, the identification of these parameters in sorting systems (grading and Automatic classification) have a particular priority Sofu et al., 2016; Zhang et al., 2021]. The need to supply high-quality products in the short term is constantly developing, and its benefits are significant for industry and commerce [Mohammadi Baneh et al., 2018]. On the other hand, grading and separating fruit based on image processing is a critical and valuable task because it improves the quality of the fruit and reduces operations in the manual process, and attention to the qualitative and essential dimensions of fruit with this technology can be achieved by adopting standard principles [Zhang et al., 2021; Baneh et al., 2023; Lu et al., 2017]. It will be used as a grading rule by implementing it with an automatic device in industrial and commercial fields.

Iranian rose apple is significant because of its good flavor and taste, its early ripening as genetic and local resources, and its good position among customers [Hassani et al., 2022]. Grading fruits and vegetables is essential for product evaluation, marketing, and processing. The uniform appearance of fruits and vegetables affects customer acceptance, sales price, and export. Fruits and vegetables are vulnerable and sensitive materials, so it is better to grade them non-destructively [Bhargava and Bansal, 2021; Nema et al., 2023]. To improve the quality of fruits and the production efficiency of Iran's rose apple sorting performance is considered an essential term for grading and categorizing agricultural products. This type of separation is based on the vital characteristics of products, such as size, color, appearance, and other factors, and this process has brought significant economic benefits to the supply of agricultural products.

In addition, introducing advanced technology and equipment for examining, grading, and separating product quality characteristics has facilitated packaging and the easy movement of products.

Grading and manual review of products and requiring a large number of workers are expensive and tasteless, and the internal characteristics of the product, whether it has arrived later or its content, cannot be evaluated, especially when the volume of the product is high; it gives variable results. The increasing demand for reliable and efficient objective methods has necessitated the supply of computer-based image processing methods. These methods have rapidly progressed recently and can quantitatively explain complex features such as size, color, and shape. The flexibility of these methods has made them an acceptable substitute for the decision-making process based on human vision [Thompson, 2008; Chithra and Henila, 2021].

Today, sorting systems under the development of various units of innovative measurement or detection systems, machine vision, grading and separation units, and other data processing units can check the size and other quality characteristics of the product with the help of the user interface and based on the definition The desired parameters have to provide acceptable yields and outputs according to the controlled statistics of a product [Nieoczym et al., 2018; Kumar and Gill, 2015].

In general, since the sorting and qualitative grading of fruits and agricultural products in terms of separation of external parameters (size, intensity, and homogeneity of color, shape, and stain, the amount of damage or corrosion of the fruit, the texture of the characteristic surface of the root or stem of the fruit and its mass) and the internal parameters (sweetness, internal diseases of the fruit or acidity) and the freshness of the fruit have been studied, so one of the essential advantages of using automatic and intelligent sorting systems is to acquire data about these critical qualitative parameters. Machine vision (Image processing system) plays a very influential role due to this technical and economic advantage in measuring and calculating these parameters [Naalbandi et al., 2016].

Several studies have been conducted on applying machine vision combined with machine learning to estimate Apple's external or internal parameters. Aladdin et al. introduced a deep learning-based image processing method for autonomous apple picking. Their system consists of a lightweight one-step recognition network for fruit recognition. It uses computer vision to analyze the point class and predict nearby positions for each fruit before harvest. Fruit recognition and sample segmentation are performed on RGB images using inputs from a high-resolution camera [Alaaudeen et al., 2017].

Unal et al. evaluated the effectiveness of deep learning (DL) models in conjunction with a near-infrared (NIR) imaging system in detecting natural bruising in Super Chief red apples immediately after harvest. They collected 1000 images for the healthy class and 500 photos for the bruised class from 500 apples. When trained on the RGB dataset, the VGG16 model achieved the highest test accuracy (86%), while the AlexNet model showed the lowest (74.6%). When AlexNet, Inception V3, and VGG16 were trained and tested on the NIR dataset, they achieved accuracy rates of 99.33, 100, and 100%, respectively [Ünal et al., 2024]. Nasoshan et al. [2023] presented an advanced digital solution using Convolutional Neural Network (CNN) technology to classify apples based on their skin color. Their CNN-based method demonstrated outstanding accuracy in recognizing apple varieties based on color, achieving an impressive 97.1% accuracy rate through rigorous testing.

According to the studies, many image processing methods combined with machine learning have successfully recognized and classified apples based on their physical or chemical characteristics. However, one of the main foundations of the success of an experimental or experimental method is its stability. One of the main bases for checking the sustainability of a method is to evaluate its environmental effects. In the studies that have been done to evaluate the physical and chemical parameters of apples using image processing, the environmental effects of these methods have yet to be mentioned. Based on this, according to the studies, the main innovation of this article is to evaluate the environmental effects of the process of detecting the hardness and acidity of Iran's Gulab apple (haze is two critical parameters in determining the ripeness of apples) by using the image processing method. This study uses the life cycle assessment method to evaluate environmental impacts.

For this purpose, this study's part of the activity aims to identify and determine the environmental factors and qualitatively determine the rose apple's physical and appearance characteristics. The next step is to determine the list of life cycle assessments and review the environmental impacts, followed by predicting environmental parameters with the help of machine learning methods.

METHODOLOGY

This part of the research presents the research method. The primary approach is to predict and estimate the parameters of the environmental effects of product hardness and acidity detection using image processing. For this purpose, 50 samples of Iranian gulab apples were prepared with completely random sizes and conditions. Further, experimental operations were carried out in line with the research objectives.

The first part summarizes the product hardness and acidity evaluation method using image processing. The second part continues this study by presenting the life cycle assessment (LCA) method for determining the quality parameters of the Apple product. Then, the hardness and acidity of the product are modeled and estimated using machine learning.

Image processing procedure

A CCD camera was used for imaging. Two circular light beams were used to provide complete and optimal light distribution to avoid shadows. Later, extracting the black background color from this fruit's angular and edge characteristics was easy, so the background was set to black throughout the imaging process. Figure 1 shows the position of the camera and this light.

MATLAB2016a software was used to implement the network algorithm. This software implemented the image parameters extraction algorithm, which included RGB extraction. Next, MATLAB R2016a software was prepared to take pictures. The CCD is sent to the computer via a USB cable and set in the illumination chamber. Then, the conveyor belt continued to move with the desired and predetermined speed on the inverter. The apples were passed under the camera and the chamber at the speed of CM15, and every time, the apple reached the center of gravity of the camera, taking pictures. It was taken online in

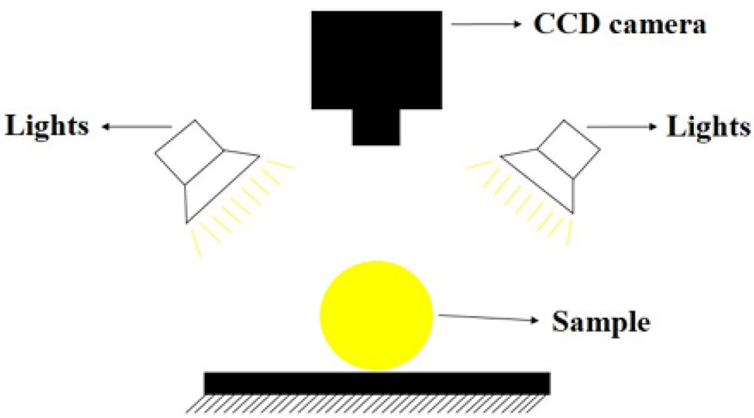

Figure 1. Schematic of the desired system

MATLAB and then saved and named in its folder. After the completion of the photography operation, image recall, pre-processing, image filtering, and step-by-step algorithm design were performed by MATLAB software, and then statistical and computational operations were performed by SPSS and Excel software to extract RGB.

Measuring firmness and pH

Table 1 provides a statistical summary of Iranian rose apple samples' firmness and acidity values. The method presented in the study by Pourdarbani et al. was used to measure firmness. In this method, a manual penetrometer device with a special probe (diameter 11 mm and height 8 mm) was used, and the probes were placed on both sides of the product [Pourdarbani et al., 2020]. Probes were pressed into the samples to record the force applied, measured in kg/cm. The average force applied on both sides of the cherry was considered a measure of stiffness. In the continuation of measuring the pH values, an acidity measuring device with an accuracy of 0.01 was used.

Life cycle assessment (LCA)

Life cycle assessment (LCA) is a specialized method utilized to assess the resources, procedures, and services involved across the production cycle, encompassing raw material acquisition, production stages, various production systems, and the potential environmental impacts of these activities. The underlying principles of LCA are detailed in a prior publication [Hashemi et al., 2023; Hashemi-Nejhad et al., 2023].

This study aims to apply LCA to examine the environmental consequences of measuring and evaluating the firmness and acidity of rose apples using image processing and predicting them through machine learning techniques. In essence, a checklist for LCA was compiled by a focus group, incorporating items such as device weight, types of devices under evaluation, their lifespan, duration of device usage for each test, and energy consumption per device.

Following the methodology outlined by Kesson et al., an allocation coefficient ranging from 0 to 1% is assigned to each entry in the process register, considering usage time and multiple uses of the entry for different reference parameters. Subsequently, the value of each analysis Analysis per amount (Apa) for every input and output is computed using Eq. 1, as Casson et al. (2020) provided [Casson et al., 2020].

$$Amount\ per\ analysis = \\ = \frac{Quantity \times Allocation\ factor}{Number\ of\ the\ analysis} \quad (1)$$

Tables 2 and 3 provide the compositions and specifications of the devices and tools used in this research and the list of evaluations in different stages for the present study.

Table 1. Values related to physical-chemical properties

Property	Unit	Maximum	Minimum	Mean	SD
Firmness	kg/cm	9.3	4.2	6.8	1.4
pH	pH	5.8	3.6	4.8	0.5

Table 2. Specifications of devices and tools us

Parameter	Composition	Weight (kg)	Electricity consumption (W)
CCD camera	80% electronic components 15% steel 5% glass	1.5	50
Cam-box	80% steel 10% electrical components 10% wood	22	30
Computer	97% electrical components 3% aluminum	1.1	64.98
pH meter	60% plastic 40% electrical components	1.5	24
Firmness gauge	10% electrical components 65% steel 15% plastic 10% aluminum	1.8	5

Table 3. Life cycle inventory (LCI)

Inputs	Quantity	Allocation factor	Lifetime		Amount per analysis	Unit
			Year	Number of analysis		
CCD camera	100	0.22	10	25000	0.000880	kg
Modeling	10	0.34	-	5000	0.000680	kg
pH analysis	100	0.19	5	7500	0.002533	kg
Firmness analysis	100	0.25	20	20000	0.001250	kg
Electricity	2.5	1	-	1	2.5	kWh
Water	2	1	-	1	2	kg
Outputs						
Experimental data	-	-	-	-	According to the scenario	
Waste material	0.75				0.75	kg

Modeling procedure

In this study, modeling was done in order to predict and estimate acidity and hardness values. The artificial neural network method and the grey wolf optimizer were used for modeling. RGB parameters were considered independent variables, and values of the life cycle's final impacts were considered dependent variables. MATLAB 2016a software was used to develop the desired network. Figure 2 shows the artificial neural network architecture integrated with the grey wolf optimizer.

According to Figure 2, the artificial neural network is initially trained with 70% of the data. Different amounts of neurons in the hidden layer were evaluated to achieve the best network architecture in network training. In the following, after choosing the most optimal number of neurons in the hidden layer, the error between the outputs and the actual values is selected as the criterion and functional function of optimization. Then, by choosing the number population, the population arrangement of the grey wolf optimizer (GWO) is set in such a way that it can adjust the biases and weights of the artificial neural network (ANN) in order to achieve the lowest error between the output and actual values in both outputs (i.e., acidity and hardness). The remaining 30% of the data is used as network test data. Two parameters, including root mean square error (RMSE) and correlation coefficient (CC), were used to evaluate the network (Equation 1 and 2).

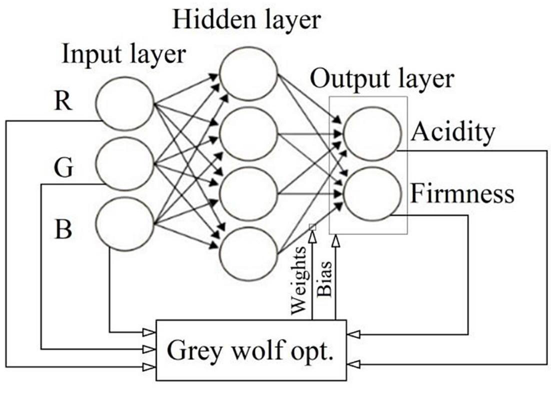

Figure 2. Integrative neural network with grey wolf

$$RMSE = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(x_i - \hat{x}_i)^2} \quad (1)$$

$$CC = \frac{Cov(x, \hat{x})}{\sigma_x \sigma_{\hat{x}}} \quad (2)$$

RESULTS

Table 4 presents the characteristics of the obtained RGB from the image processing analyses. According to Table 4, R has the highest mean value

Table 4. The main characteristics of the obtained RGB from image processing

Property	Mean	Min	Max	SD
R	13.73	144.44	75.31	120.75
G	13.33	174.91	92.91	156.44
B	6.72	60.79	24.77	46.31

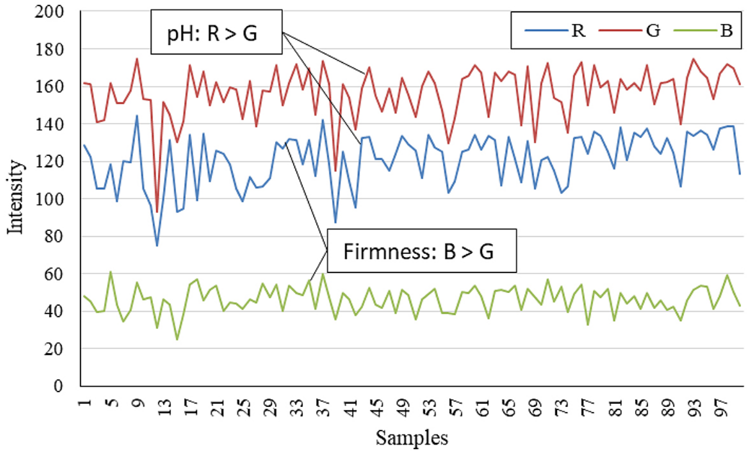

Figure 3. The variation of RGB measuring

(13.73) while B has the lowest mean value (6.72). Figure 3 presents the variation of the RGB measuring. The output of the feature selection technique indicated that, pH values are affected by R and G while firmness is affected by B and G. In the context of image processing, the coloration of yellow apples can indicate their ripeness, which in turn influences their acidity. Typically, green apples have higher acidity due to their lower sugar content and higher concentration of malic acid. As apples ripen, they transition from green to yellow and, in some cases, develop red or blush tones. This shift in color is associated with a decrease in acidity as sugar content increases. Thus, in image processing, if acidity values follow the red and green color spectrum, it suggests that greener shades correlate with higher acidity, while redder or yellower shades point towards lower acidity and increased ripeness.

This observation is useful in image processing as it allows for a non-invasive way to estimate the ripeness and acidity of yellow apples. By analyzing color data in an image – specifically, the red and green color channels – it's possible to predict the acidity level. For instance, an apple that leans toward the greener end of the spectrum may be assessed as less ripe and more acidic, while those with redder hues might be considered riper with lower acidity. This relationship provides a practical framework for assessing apple quality, optimizing harvest times, and ensuring consistent flavor profiles in the food industry.

On the other hand, the correlation between firmness values and the blue and green color spectrum likely relates to the characteristics of apples at different stages of ripeness. Apples with a blue-green hue often indicate a firmer texture because they are typically less ripe and have a higher cell turgor, the pressure within the cells that gives the fruit its firmness. As apples ripen, their color shifts from green to yellow and, in some cases, to orange or reddish tones, while their internal

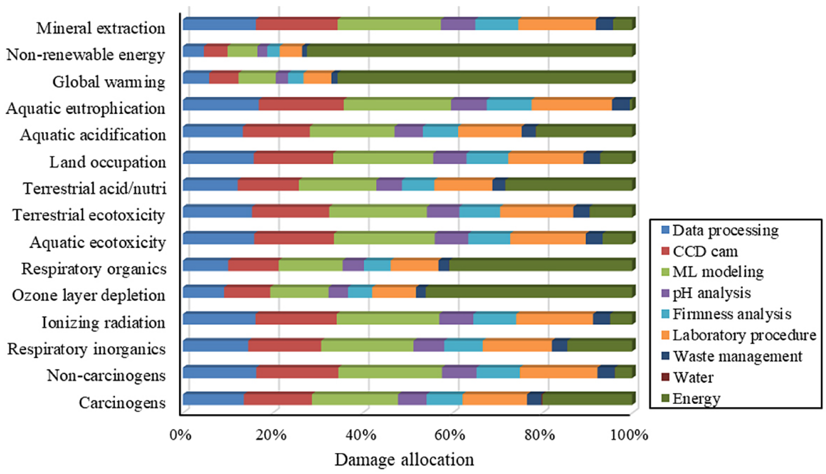

Figure 4. Mid-point environmental impacts of yellow apple image processing

structure changes. The cell walls begin to break down, reducing turgor pressure, which leads to a softer, less firm apple. Thus, in image processing, a spectrum of blue to green may suggest firmer apples, with greener hues generally indicating a crisper texture.

This correlation is useful in the context of image processing because it provides a non-invasive method to estimate the firmness of yellow apples. By analyzing the blue and green color spectrum in apple images, researchers or producers can infer the apple's texture without physically testing it. For example, apples with a distinct blue-green tint are likely to be firmer and crisper, making them ideal for long-term storage or certain culinary applications. In contrast, apples with less pronounced blue or green hues and more yellow or reddish tones could be softer and better suited for immediate consumption or processing into products like applesauce. This analysis approach supports quality control, optimizing apple sorting, and ensuring consistent product characteristics in food production.

Life cycle assessment (LCA)

Figure 4 categorizes the input values of the image processing for detecting the firmness and pH values in terms of the environmental mid-point impacts. As is clear from Figure 4, water and energy followed by laboratory processes have the highest mid-point environmental impacts.

Table 5 compares firmness and pH analysis from the view point of mid-point environmental impacts. According to Table 5, the environmental impacts of the firmness analysis is higher than that for the pH analysis.

It is due to the high portion of input values of the inventory for firmness analysis in comparison with that for the pH analysis. This claim can be confirmed by Figure 5. Figure 5 categorizes the environmental impacts of the firmness and pH analysis into for sets of the endpoint impacts. According to Figure 5, resources followed by human health and climate change have owned the highest portion of the endpoint impacts for analyzing the Firmness and pH values. While ecosystem quality has the lowest portion.

The prominence of resources, human health, and climate change in endpoint impacts when analyzing the firmness and pH values of yellow apples can be explained by the interconnected nature of agricultural practices, resource utilization, and human well-being. Resources refer to inputs like water, energy, fertilizers, and pesticides used in apple cultivation. The choice and usage of these resources can significantly affect both the quality of the apples and broader environmental impacts. For example, specific fertilizers can influence soil chemistry, affecting pH levels in apples. Similarly, irrigation and energy usage can impact the firmness of the fruit. These factors reflect how resource management and agricultural practices play a central role in shaping

Table 5. The comparison of analyses from the mid-point environmental impact point of view

Impact category	Unit	Firmness analysis	pH analysis
Carcinogens	kg C_2H_3Cl eq	0.011526	0.012833
Non-carcinogens	kg C_2H_3Cl eq	0.039841	0.047897
Respiratory inorganics	kg PM2.5 eq	0.001204	0.001379
Ionizing radiation	Bq C-14 eq	8.308479	9.943197
Ozone layer depletion	kg CFC-11 eq	1.13E-07	1.08E-07
Respiratory organics	kg C_2H_4 eq	0.000257	0.000254
Aquatic ecotoxicity	kg TEG water	305.1638	362.4942
Terrestrial ecotoxicity	kg TEG soil	50.97971	59.7621
Terrestrial acid/nutri	kg SO_2 eq	0.017368	0.018515
Land occupation	m2org.arable	0.01668	0.019764
Aquatic acidification	kg SO_2 eq	0.003979	0.0044
Aquatic eutrophication	kg PO_4 P-lim	0.002617	0.003192
Global warming	kg CO_2 eq	1.40517	1.151923
Non-renewable energy	MJ primary	24.95054	19.17875
Mineral extraction	MJ surplus	0.104206	0.125004

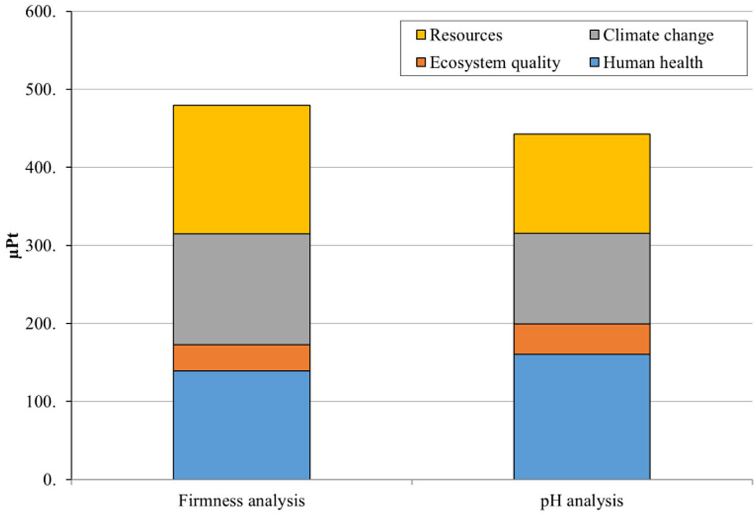

Figure 5. The environmental impacts of the firmness and pH analysis

the endpoint impacts, accounting for their significant portion in this context.

Human health emerges as another significant endpoint impact due to the direct relationship between agricultural inputs and consumer safety. The use of pesticides, for example, can lead to residues on apple skins, impacting human health if not properly managed. Additionally, the handling and processing of apples might affect nutritional content, including pH-related characteristics, influencing overall human health outcomes. Climate change plays a pivotal role as it affects growing conditions—temperature, rainfall patterns, and seasonal shifts—which in turn impacts apple firmness and pH. These broader climate patterns also influence resource use and human health. Ecosystem quality may have a lower portion in these endpoint impacts because, while agricultural practices can affect biodiversity and ecosystem services, the primary focus in analyzing firmness and pH values might not immediately extend to these broader ecological concerns.

Modeling

Table 6 presents the training process of the proposed model with 22 neurons in hidden layer and 150 population during 500 iteration number. In the following, Figure 6 presents the validation results of the proposed model in testing process. According to the findings, the proposed model could successfully cope with the prediction of the environmental impacts of the pH and Firmness values.

At this stage, this difference in accuracy can be related to the inherent characteristics of pH measurement as a chemical property, which can be directly and more reliably related to specific spectral or colorimetric characteristics in the images. This trend was also identified in various studies that have studied other products. In the study conducted by Gómez et al. [2006] it was observed that the correlation coefficient of prediction of acidity values was slightly higher than the firmness of Satsuma mandarin product with the help of spectroscopic method. Also, in the study conducted by Li et al. [2010], the correlation coefficient

Table 6. The main findings of the training process of the proposed model

Parameter		RMSE	CC
pH	Human health	2.03E-08	0.95
	Ecosystem quality	0.0021	0.96
	Climate change	0.021	0.97
	Resources	1.297	0.96
Firmness	Human health	2.98E-08	0.94
	Ecosystem quality	0.0031	0.92
	Climate change	0.023	0.94
	Resources	0.314	0.92

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	Ecosystem quality	0.0031	0.92
	Climate change	0.023	0.94
	Resources	0.314	0.92

of pH measurement with the help of spectroscopic method was slightly higher than the firmness of Dangshan' pear product and its ripening.

Based on the investigations, it can be said that characteristics such as color intensity are relatively consistent and less influenced by external factors compared to the characteristics used to evaluate product hardness. This consistency allows the predictive model to more accurately learn and predict pH levels, resulting in higher measurement accuracy.

On the other hand, the characteristics of pH and strength data are significantly different. Acidity levels, as measured by pH, can typically show clearer, more uniform and recognizable patterns that can be easier for a machine learning model to interpret. The uniformity in the pH data means that the neural network can effectively map the input features to the output values more accurately. In contrast, firmness is a mechanical property that is influenced by several factors, including structural integrity, maturity, and texture of the fruit. These factors can introduce a higher degree of variability and complexity into the data, making it challenging for the neural network integrated with the grey wolf algorithm to accurately model it. Complex and less uniform patterns in strength data can make it more difficult to generalize and lead to low prediction accuracy.

This study looks at the non-destructive evaluation of apple quality from another angle. According to the promising results obtained from the environmental assessment, this approach can be placed next to the advantages of other non-destructive methods and make it more preferable than the conventional methods of apple quality assessment.

According to the results obtained, Energy can be identified as the most important input affects the environmental impacts of yellow apple image processing. The studies conducted in the field of environmental assessment of non-destructive testing of the properties of fruits and agricultural products are limited despite their importance. The similar results obtained by Casson et al. [2020] in analyzing the environmental advantages of spectroscopy method for the prediction of intact olive ripeness. Accordingly, Energy was identified as an effective input in the environmental assessment of non-destructive measurement of apple properties primarily due to its pivotal role in powering the advanced technologies used in these processes. The image processing and computational analysis rely heavily on sophisticated equipment and computational resources, which in turn depend on a steady and significant energy supply. The integrated neural network and grey wolf optimization method, which enhance the precision and reliability of these measurements, require substantial computational power for data processing and analysis. Hence, energy consumption becomes a critical factor to consider, as it directly impacts the overall efficiency and sustainability of the quality assessment system. On the other hand, assessing energy as a primary input allows for a comprehensive evaluation of the environmental impact associated with these technologies. By focusing on energy consumption, the study can identify potential areas for improvement in terms of energy efficiency, which is crucial for reducing the carbon footprint and enhancing the sustainability of agricultural practices. Energy efficiency not only translates to cost savings but also aligns with global efforts to minimize environmental impacts. As the agricultural sector moves towards more technologically advanced methods, understanding and optimizing energy use becomes essential for ensuring that these innovations contribute positively to environmental sustainability goals. Thus, energy stands out as a critical input, providing a clear pathway for improving both the

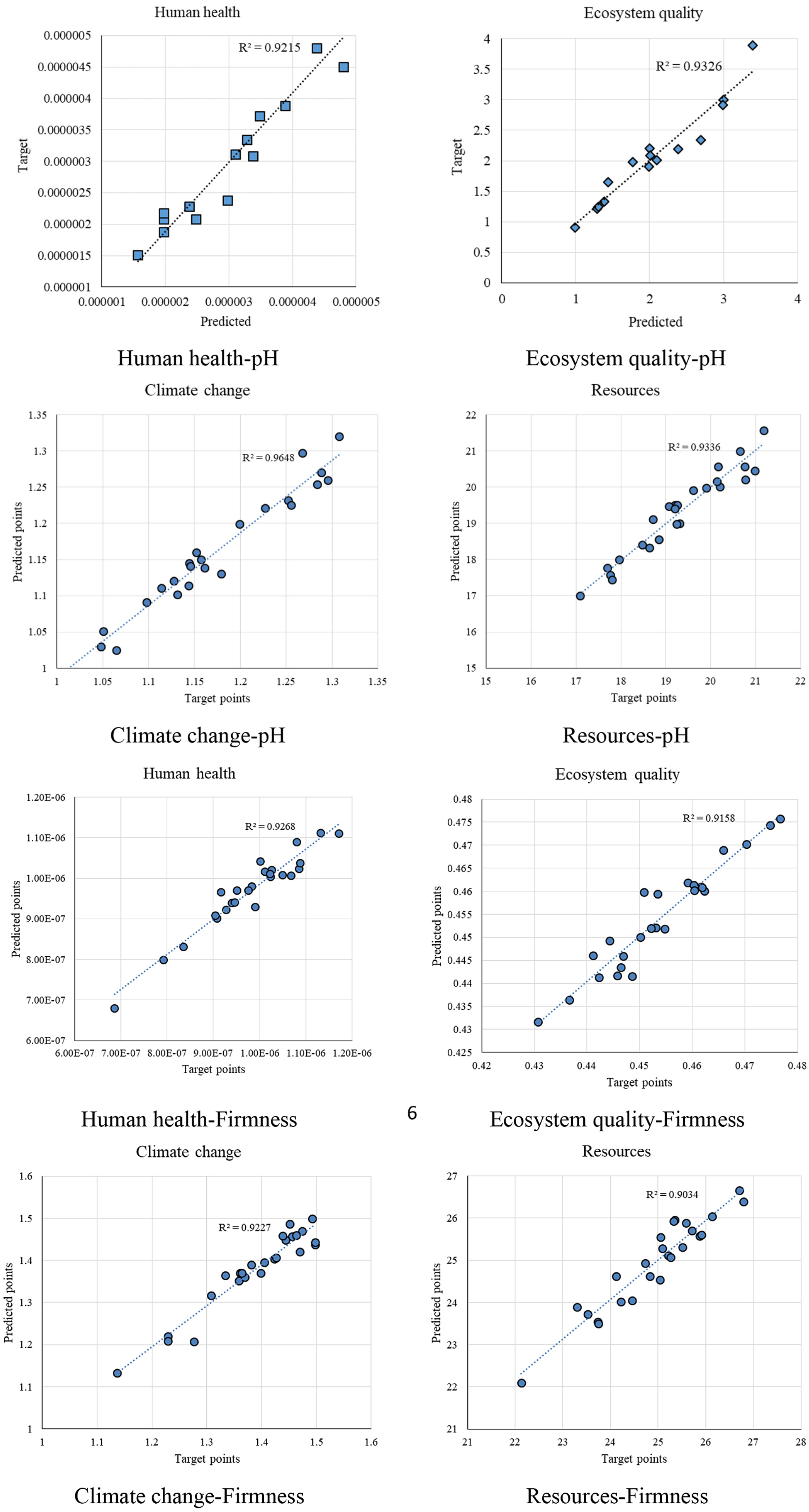

Figure 6. Testing results of the proposed model for prediction of the end-point impacts

environmental and economic aspects of non-destructive measurement techniques.

For this problem, we consulted with a focus group of experts in the field of energy (3 people), artificial intelligence (3 people) and specialists in non-destructive evaluation of the properties of fruits and agricultural products (3 people) and solutions were presented in this field. Due to the fact that each of the experts provided a solution from the point of view of their own expertise, three different scenarios were obtained. Energy experts shifted the source of energy supply towards renewable energies. So that with this method they could justify the management of the carbon cycle and prevent the release of pollutants. On the other hand, experts in the field of artificial intelligence emphasized the use of algorithms with high efficiency and at the same time low computational load in order to increase the efficiency and reduce the duration of the computer hardware performance. Finally, experts in the field of non-destructive diagnosis emphasized the use of green computing methods such as turning off idle systems or using low-power modes to provide a solution to reduce energy consumption.

CONCLUSIONS

The study on evaluating the life cycle of determining the firmness and acidity of rose apples through image processing and utilizing an integrated neural network with the grey wolf optimization method has provided valuable insights into the intersection of agricultural quality analysis and environmental impact prediction. The use of image processing techniques combined with advanced neural network algorithms offers an efficient and non-invasive approach to assessing key fruit quality attributes, potentially reducing the need for destructive testing and expediting the process. The integration of grey wolf optimization within the neural network architecture has further enhanced the predictive capabilities, allowing for more accurate assessments with fewer computational resources. The findings suggest that this approach could serve as a robust tool for apple quality analysis, providing benefits not only in terms of assessing firmness and acidity but also in minimizing the environmental footprint. By leveraging machine learning and optimization techniques, this method has the potential to streamline agricultural practices, reduce waste, and improve resource efficiency. Looking toward the future, several key areas offer promising directions for further research and development. Firstly, the integration of additional data sources, such as climate and soil information, could enrich the predictive models and improve accuracy. Additionally, exploring the applicability of this approach across different apple varieties and other fruit types could expand its utility. There is also the opportunity to delve deeper into the environmental implications, assessing how this method can contribute to sustainable practices in agriculture, particularly in reducing resource use and environmental impact. Another promising avenue for future research is the development of more sophisticated models that incorporate additional machine learning techniques, like deep learning, to further enhance accuracy and robustness. Collaborative efforts between agricultural scientists, environmental experts, and data scientists will be essential to drive innovation and ensure the application of these advanced methodologies benefits both the agricultural sector and the environment. Ultimately, this study underscores the potential for advanced image processing and neural network-based methods to revolutionize agricultural quality assessment, contributing to more efficient, sustainable, and environmentally conscious practices in the industry.

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